The Driver's Steering Feel Assessment Using EEG and EMG signals

Gao Zhenhai, Fan Da[*]

ABSTRACT

Whereas the existing steering feel evaluation methods fail to objectively describe subjective feelings, this paper successfully implements physiological features analysis of both mental and physical workload. Several drivers were invited to attend double-lane change tests, during which the electroencephalogram and surface electromyogram signals of their shoulder muscles were obtained. The steering feel was rated subjectively after each test run. Through the comparison of subjective ratings, it was found that physiological features of both mental and physical workload were correlated with maneuverability and lane-change ability. This research sheds new light on measuring driver's response in performance evaluation and provides valuable references for steering feel quantification.

Introduction

Car driver is responsible for the perception of environmental information and vehicle control which is an essential part in the closed-loop system. Drivers in the driving control need to focus, analyze condition of both traffic and ego vehicle, make the correct driving strategy and apply the appropriate driving action. Therefore, car driving not only needs the driver to pay a certain amount of physical strength but also need to bear a certain degree of mental load. When the load is too high, it may lead to errors in the decision-making or operation, resulting in traffic accidents.

The steering feel, in essence, results from the interaction between the driver and the vehicle. As the driver controls the vehicle with the steering wheel, he receives feedback from the steering wheel and vehicle body. The keystone of steering feels research lies in quantification. Before system design and calibration, it is necessary to establish the quantitative variables for measuring the steer feel.

The traditional performance evaluation methods cover the following steps. First, the driver, as the most powerful "sensor", acquires force feedback from the steering system and combines it with the feedback from other body parts to form subjective feelings. Then, the subjective feelings of the driver, together with the objective metrics of vehicle handling, lay the basis for steering feel evaluation. The vehicle handling metrics are measured and analyzed against certain standards in proving ground tests, and the subjective feelings are rated according to the driver's experience in different tests (Data *et al.,* 2002; Zhang *et al.,* 2009; Matsushita *et al.,* 1980).

The evaluation methods stated above have many defects. In the objective evaluation, the driver acts as an automatic pilot to accomplish certain driving maneuvers, and the vehicle handling metrics are not directly mapped

Corresponding author: Fan Da
Address: State Key Laboratory of Automotive Simulation and Control, Jilin University, Changchun, China
e-mail ✉ fandath@qq.com

6

to subjective feelings. In the subjective evaluation, the subjective ratings are in lack of consistency and discreteness, due to the mental and physical differences among drivers (Lin *et al.,* 2007; Zong *et al.,* 2000)

As a matter of fact, steering maneuver is accomplished under the control of the driver's central nervous system, while subjective feelings arise from the feedback information transmitted via the trunk, limbs and other bodily parts. Therefore, the driver's physiological reactions directly bear on different steering maneuvers and subjective feelings. This calls for further investigation into the driver's psychophysiological features which are related with driver's mental workload and physical workload.

The concept of mental workload starts in the area of human factor research. The ISO10075-3 standard defines this concept. In this standard, mental workload is divided into two parts: mental strain and mental stress. Mental stress is defined as the sum of all external influences on the mind; mental stain is defined as the immediate effect of stress, depending on the individual's behavior, personality and other internal factors. This definition explains the mental load from both internal and external aspects.

The evaluation methods of mental load can be summarized into three categories: the subjective scoring evaluation method, the manipulative performance evaluation method and the psychophysiological evaluation method.

The subjective evaluation of mental load is mainly carried out by means of subjective scoring. It is a psychological method to describe and explain the subject's subjective feelings. It is widely used in the aspects of emotion, fatigue and acceptability evaluation.

Objective assessment of mental load can be divided into performance evaluation method and psychological evaluation method. The indicators of performance usually include the accuracy, reaction time and operation error. For driving a car, these indicators include steering wheel angle, accelerator pedal position, brake pedal position and other indexes directly caused by the driver's operation.

In recent years, with the development of physiological testing technology and sensing technology, the method of using the physiological parameters to evaluate the driver's mental workload has drawn more and more attention from researchers in the automotive field.

The use of physiological signals to evaluate the mental load is essentially the study of the impact of psychological status on human physiological status. In general, the physiological signals of different human bodies according to the mechanism of production can be divided into two types: physiological signals associated with the Central Nervous System (CNS), including EEG (Electroencephalogram), electrooculogram (EOG, Electrooculogram), magnetic field activity and metabolic activity of the brain; physiological signals associated with the Peripheral Nervous System (PNS), specifically including EDA (Electrodermal Activity), ECG Electrocardio), respiratory signals, body surface temperature and pupil diameter and so on.

EEG signals are spontaneous, rhythmic electrical activity of brain cell populations and are recorded by electrodes placed on the surface of the scalp. EEG signals are generally divided into two types: spontaneous EEG and Event Related Potentials (ERP). Spontaneous EEG activity usually refers to the absence of external stimuli in the case of EEG activity, the signal bandwidth is usually from 1Hz to 100Hz. EEG signals generated during a particular task (e.g. responses to current, visual, audible, or imagined stimuli) are referred to as evoked potentials or event-related potentials.

In car driving, Lei *et al.,* analyzed the driver's EEG signal under lane change conditions and found different principles of EEG under different mental workload which validated the effectiveness of EEG in evaluating the driver's mental workload and sensitivity. Nissan's Gheorghe *et al*. evaluated the mental load during human-computer interaction using the P3 latency index of event-related potentials and found that the P3 latency index was unaffected by external loads. Yang *et al.* used the virtual reality technology to establish different traffic scenarios and used EEG and pattern recognition technology to analyze the driver's cognitive status. Brookhuis and Waard *et al.* used the driving simulator to design different driving conditions, recorded ECG and EEG signals and found that the alpha frequency band in EEG was well correlated with the driver's mental workload.

One of the options for dealing with physical workload is surface electromyography (EMG). The technique has been applied to various fields, including driver behaviour, biomechanical mechanism, comfort, safety, etc. Much research has been done on surface EMG in recent years. For

7

example, the Driver-Vehicle Dynamics Group at Cambridge University employed the technique to analyse the neuromuscular mechanism and muscle contraction features, and construct the driver model with neuromuscular features (Pick *et al.,* 2007). Stefan Haufe predicted emergency braking using electroencephalography and surface EMG, and achieved an earlier trigger time compared with the prediction based on brake pedal movement (Haufe *et al.,* 2011). With non-intrusive feature, surface EMG was also applied in ergonomics design through frequency spectral analysis (Mastrigt *et al.,* 2015; Kolich, 2014), and in injury mechanism research for vehicle crashes (Gao *et al.,* 2015, 2016).

Focusing on the principles of the driver's physiological features, the abovementioned studies give no though to the relationship between vehicle performance evaluation and physiological features. In fact, the physiological reactions of the driver and occupants can be mapped to vehicle performance. After collecting the surface EMG signals of an occupant's neck and back muscles, Farah discovered that fast lateral acceleration leads to intense muscle activity and low comfort of the occupant, and suggested taking muscle activity as the indicator of occupant's comfort and limiting lateral acceleration to improve the comfort (Farah *et al.,* 2006). Zheng calculated the activity of sternocleidomastoid muscle in simulated driving; pointing out that the driving comfort is negatively correlated with muscle activity (Zheng *et al.,* 2013). Seung-Min Moa measured both vehicle handling metrics and surface EMG signals of shoulder muscles, examined the correlation between the typical parameters of the metrics and signals, and found the close connections of muscle activity with steering angle, steering force and lateral acceleration (Moa *et al.,* 2012).

Despite the above studies, there is still no method to evaluate the subjective feel based on the driver's physiological features. To bridge the gap, this paper explores the relationship between subjective feel and the physiological reactions of the driver. The EEG and surface EMG signals of shoulder muscles were measured when the driver drove three different vehicles. Several double-lane change tests were conducted to rate the subjective feel of each test vehicle. Then, the author analyzed the mapping relationship between subjective feel and typical physiological features. This research provides guidelines for the

evaluation and test of steering feel based on physiological features.

Methods
With the development of steering system, maneuverability and stability have been replaced by lane-change ability, on-center steering feel and driving comfort as the key determinants of steering feel. In general, the evaluation of steering feel mainly involves four aspects: accuracy, sensitivity, stability and comfort.

Each of the aspects corresponds to a specific type of test. The accuracy and sensitivity are evaluated by lane-change and on-center steering tests, respectively. The stability is mainly assessed through returnability test. The maneuverability test is the primary tool of comfort evaluation. Considering the limit of the proving ground, the double lane-change test was selected to reflect the steering accuracy and comfort.

The test course was set according to ISO/3888-1 1999 Passenger Cars: Test Track for a Severe Lane-Change Manoeuver. Every driver was required to complete a set of 15 successful tests with each test vehicle. Each set of successful tests contained 5 tests at 40km/h, 5 at 60km/h and 5 at 80km/h. In each set, surface EMG signals were measured from the shoulder muscles of each driver. At the completion of a set of tests, the driver was asked about his subjective rating for the test vehicle.

Three vehicles were tested, including an A-class sedan (2012 FAW Oley, L4, 1.5L engine, manual gearbox, hydraulic steering), a hatchback (2011 Toyota Yaris, L4, 1.6L engine, manual gearbox, electric steering) and a compact SUV (2012 Nissan Qashqai, L4, 2.0L engine, CVT, electric steering). The vehicles were expected to exhibit significantly different steering feels.

Six experienced male drivers who had held a driving license for 10~16 years participated in the tests. All of them worked at the R&D center of FAW Group Corporation and were familiar with the subjective evaluation of steering feel and double lane-change test. The participants were 35.5±7.5 years of age, 171±4.2 cm in height, and weighed 74.5±8 kg.

The focus of subjective evaluation has shifted to performance and comfort, and the evaluation of steering feel generally involves such four aspects as accuracy, sensitivity, stability and comfort. However, the subjective evaluation of steering feel can be further split into

maneuverability, returnability, sensitivity, correction effort, accuracy, road feel, rolling feel and effort. To prepare for subject rating, the evaluation results were improved statistically, a multilevel evaluation structure was created by analytic hierarchy process, and a weight matrix was established. With steering feel as the element of the goal layer, maneuverability, returnability, on-center steering performance and lane-change ability were selected as elements of the criteria layer as shown in Table 1 (Shi *et al.,* 2007).

Table 1. Subjective evaluation items

Level 1	Level 2	Level 3
Steering feel	Maneuverability	
	Lane change ability	Accuracy
		Rolling feel
		Effort

A low mass, moment of inertia 01184 IR steering effort sensor (Sensor Development Inc.) was mounted on the steering wheel of each test vehicle (Figure 1). The steering torque and angular position of the steering wheel were measured during the test. The steering wheel was fitted with a 10-inch through-hole for uninhibited deployment of an air bag, preventing the projection of the sensor at the diver. To measure steering torque, an infra-red telemetry transmission system was built that permits unlimited wheel rotation. The angular steering position sensor was mounted on the inside of the front windshield as an optical encoder. Furthermore, a drive train assembly rotated the drive shaft attached to the encoder once the steering wheel sensor was turned on.

Figure 1. Low mass, moment of inertia steering effort sensor

Steering maneuvers are directly manipulated by muscles and joints of the upper limbs, mainly the muscles around the shoulder and elbow joints. Researchers have dug deep into the key muscles involved in steering maneuverability and their

biomechanical principles. Inspired by the work of D. J. Cole and Liu Yahui, surface EMG signals were measured from the anterior and mid portions of the deltoid, sternal portion of pectoralis major and long head of triceps.

During driving, the main sources of interference of the driver's EEG signals are vibration signals and EOG signals which is especially obvious.

According to the characteristics of the driving task and the purpose of the experiment. EEG test electrodes were arranged in accordance with the international 10-20 system shown in Figure 2. The electrodes were arranged according to the scalp 4 standard points which were the nasal root, occipital protuberance, 10% and 20% points of the distance between the left and right ear.

In this paper, the accuracy and anti-jamming ability of EEG signal test were considered. Bipolar lead test method and Bionomadix system feature were used to select F7 and F8 locations as shown in Figure 2 as EEG test points.

Figure 2. Electrodes arrangement of EEG signal test

Electrooculogram is caused by the human eye movement in the human skin surface changes in potential. Biomedical engineering studies have found that the potential difference between the retina and the cornea is the cause of ocular electrical signals, which in turn arise from the electrical activity of the pigment epithelium and photoreceptors in the retina.

In order to obtain effective EOG signals, two pairs of electrodes were required to be arranged near the eyeball. One of the electrodes was the reference electrode, and the change of the potential measured by the other electrode was equal to the change of the potential difference between the pair of electrodes which was the change of EOG signals.

Through the study of eye movement during driving (Polychronopoulos *et al.,* 2007), when the driver observes the road conditions to

9

obtain the external traffic environment information, the eye movement mainly focuses on horizontal saccade. Therefore, this paper focused on the horizontal movement of the eyeball and the resulting changes in the eye electricity. The bipolar lead was used to collect the driver's EOG signals during the test. The two electrodes were arranged on the outer edges of the left and right orbits and kept in a straight line with the eyeball. The change of the potential difference during the horizontal movement of the eyeball was recorded.

MP150 wireless surface EMG devices (Biopac Sytems, Inc.) were adopted for the measurement. Ag/AgCl electrodes were attached on the bulk of the said contracted muscles. The skin was wiped with rubbing alcohol and removed of any hair to maintain a low resistance. Then, the electrodes were connected to the pre-amplifier capable of wireless signal transmission (Figure 3). In addition, a digital FIR filter was used to prevent strenuous movement of the wire from generating artifact. The band-pass filtering was set to 10~250Hz (De Luca, 1997).

Figure 3. Measurement of surface EMG signals from shoulder muscles

Concerning the physical differences (i.e., adipose layer, skin resistance, etc.) between drivers, the surface EMG signals were normalized by 100% maximum voluntary contraction (MVC). The normalization method calculates the amplitude ratio of the measured surface EMG signals to those at the MVC. All drivers were trained to perform the MVC before the tests (Sinclair *et al.,* 2015).

Results
In this paper, independent component analysis was used for the removal of ECG artifact. Independence Component Analyze (ICA) is a signal processing method based on blind source separation technology. This method decomposes the original signal into several independent components according to the principle of statistical independence through a specific optimization algorithm so as to enhance and analyze the signal. The acquired EEG signal is a linear combination of spontaneous EEG signals and various artifacts, which satisfies the condition of signal source independence. Therefore, this method is very suitable for EEG signal processing.

The surface EMG signals produced at maximum voluntary contraction were measured during each test run, and interpreted by their root mean square (RMS) value. The muscle activity was defined as the RMS ratio between the surface EMG signals measured in the test and those at the MVC.

The accurate motion control relies on the simultaneous contraction of two opposing muscles, namely, the agonist and antagonist. When the driver is at the wheel, the muscles of his upper limbs contract and contribute different efforts during the movement. A relatively intense muscle co-contraction is required for accurate steering movement. In this paper, the agonist and antagonist are categorized by the positive or negative steering torque they produced.
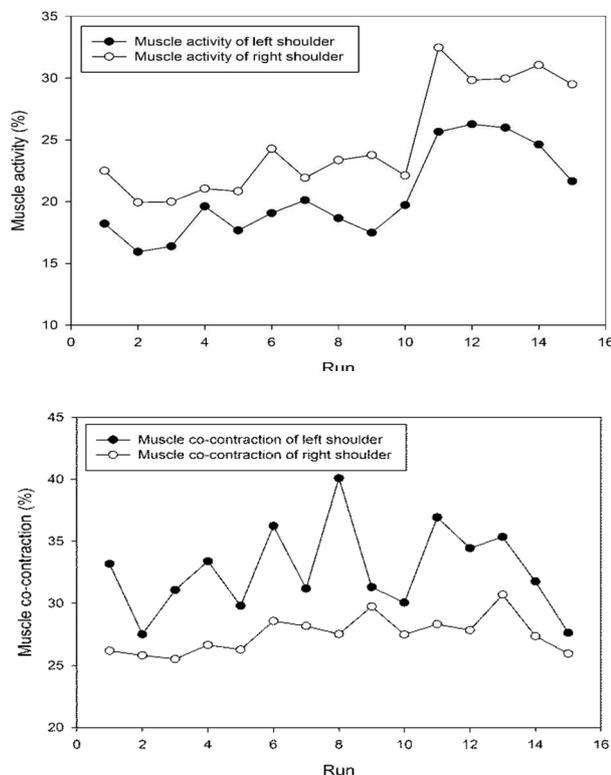
Figure 4. Average muscle co-contraction of both shoulders in each run

Four muscles showed significant contractions in all the runs, namely the long head of the triceps and the anterior portion of the deltoid of both shoulders. Figure 4 illustrates the muscle activity and muscle co-contraction at different test speeds. Overall, test vehicle 2 maintained the minimum muscle activity, while test vehicle 3 boasted the maximum muscle activity at each test speed. However, muscle co-contraction obeyed a different pattern. At each test speed, the minimum muscle co-contraction was found in test vehicle 1 rather than test vehicle 2, while the maximum muscle co-contraction still belonged to test vehicle 3. It was assumed that the features of muscle activity and muscle co-contraction can convey different physiological meanings and the driver's states.

An analysis of variance (ANOVA) was performed on the physiological features and the type of test vehicles. In general, two variables have a significant correlation if the P-value is less than 0.05. In light of the results in Table 2, the type of test vehicle had a significant effect on the physiological features, indicating that the driver is bound to make different physiological reactions at the wheel of different vehicles.

Table 2. ANOVA on physiological features and test vehicle types

Physiological Parameters	p-value
Amplitude of alpha band of EEG	<0.001
Muscle activity of left shoulder	<0.001
Muscle activity of right shoulder	<0.001
Muscle co-contraction of left shoulder	<0.001
Muscle co-contraction of right shoulder	<0.001

The dynamic changes of EEG signals during steering maneuver when driving different vehicles were analyzed. It was found that the vehicle type had an effect on the amplitude of the alpha band (p = 0.001). A paired t-test showed that the power spectrum of alpha band when driving vehicle 3 was slightly decreased when driving other vehicles (p = 0.001).

Table 3. Subjective ratings of maneuverability and lane-change ability

	Test vehicle 1	Test vehicle 2	Test vehicle 3
Maneuverability	7	7.25	6.25
Lane-change ability	7.07	6.53	6.11
-Accuracy	7.25	6.5	6.125
-Rolling feel	7.25	6.25	5.75
-Effort	6.5	6.75	6.25

The analytic hierarchy process was introduced to calculate the weight of each rating. Table 3 lists the ratings on the elements of the criteria and alternatives layers. test vehicles 2 and 3 came at the top and bottom of maneuverability rating, respectively. As for lane-change ability, test vehicle 1 received the highest rating while test vehicle 3 was still at the bottom. In the criteria layer, test vehicle 1 came first on accuracy and rolling feel, test vehicle ranked first in effort, while test vehicle 3 had the lowest rating in every aspect.

Discussion

The subjective evaluation is grounded on the driver's feelings on completing driving tasks with a vehicle. The results of subjective evaluation may vary with the mental and physical conditions of drivers. To reduce discreetness and enhance reliability, there should be at least 10 drivers taking part in the evaluation. A qualified and skilled test driver must be familiar with the test vehicle, make accurate judgment, and express their view clearly. The external noises must also be avoided.

Qualitative and quantitative evaluations are two common methods of subjective evaluation. Qualitative evaluation often ranks different test vehicles in order, while quantitative evaluation gives relative and absolute ratings. The relative ratings are given in relation to a benchmark. The absolute ratings are made in reference to different rating scales, such as the Cooper–Harper rating scale. These rating scales were first used in the aerospace industry, and later adopted in the automotive industry. Despite the introduction of quantitative ratings, the subjective evaluation is still not enough quantified. The ratings are not directly related to vehicle dynamics, which can be predicted in simulation. What is worse, subjective evaluation takes a long time and requires many professional test drivers.

In objective evaluation, maneuverability and stability are usually measured by steering force and steering angle. The lateral acceleration and yaw rate are also popular parameters in objective evaluation. Nevertheless, these objective parameters are not intuitional enough to describe the driver's subjective feelings. Some scholars have explored the correlation between vehicle handling metrics and subjective feelings, but failed to ascertain any quantitative mapping relationship (Rothhämel *et al.,* 2011). Therefore, the steering feel was evaluated by a novel quantitative method.

It is known that the driver's mental workload is related with EEG signals especially

the alpha band and theta band. Normally the mental workload of the driver was tested when the driver performed both driving-related tasks and non-driving-related tasks. However the task difficulty was also convinced to have an effect on EEG signals according to Smith's study (Smith *et al.,* 2001).

In this paper, different vehicle types resulted in different steering feel which was related with the task difficulty. The double-lane change test was required the driver to be fully concentrated. Therefore, the different EEG signal features were found when driving different vehicles even non-driving-related tasks were performed. The difficulty of driving task shown by EEG signals was consistent with subjective ratings. Driving vehicle 3 to complete the double-lane change test was seemed to be the most difficult task.

As an indicator of the use of muscle strength, muscle activity is closely related to energy consumption. G. Farah and Rencheng Zheng used to depict the driving comfort and resistance to lateral acceleration with muscle activity; the test subjects were not comfortable at intense muscle activity (Farah *et al.,* 2006; Zheng *et al.,* 2013). Similar to comfort, it may be assumed that muscle activity is correlated with steering maneuverability. This assumption is validated by the previous observations that test vehicle 2 had the minimum muscle activity and highest maneuverability rating, while test vehicle 3 had the maximum muscle activity and lowest maneuverability rating.

Furthermore, muscle activity is significantly correlated with steering torque, an objective indicator of maneuverability evaluation (Moa *et al.,* 2012). Hence, muscle activity can serve as a quantitative parameter of maneuverability. The muscle contraction required for higher steering force may lead to more intense muscle activity.

Muscle co-contraction refers to the simultaneous contraction of the agonist and antagonist. It is fundamental to the accurate motion control of human body. As stated by Cole, the drivers more familiar with the test vehicle make less intense muscle co-contraction and fewer path error (Pick *et al.,* 2007), indicating the importance of learning. The driver tends to perform well with low muscle co-contraction, and the muscle co-contraction can be calculated in a similar way to steering efficiency (Liu, 2014).

These findings facilitate the objective evaluation of steering comfort.

In this research, test vehicle 1 had the highest rating of lane-change ability and lowest muscle co-contraction. This means the vehicle can make accurate lane-change maneuvering with a low amount of muscle co-contraction. The muscle co-contraction also relaxes with a preferable rolling feeling, which enables the driver to make a clear judgement of the dynamics and performance of the current vehicle. Of course, minimum muscle co-contraction is not always the twin of minimum muscle activity. For instance, test vehicle 2 had the minimum muscle activity, but edged out test vehicle 1 in muscle co-contraction.

To sum up, muscle co-contraction is closely related to lane change ability in subjective ratings. Thus, it is possible to quantify vehicle drivability, especially lane-change ability, with muscle co-contraction.

Conclusion

This paper carried out a double lane-change test to evaluate the steering feel of three test vehicles, measured the EEG signals and surface EMG signals of the driver's shoulder muscles, and performed subjective ratings after each run. The EEG signals especially alpha wave bands were affected by different vehicle types. Relatively high muscle activity was observed in the long head of triceps and the anterior portion of the deltoids during driving. After comparing subjective ratings with typical physiological features, it is learned that vehicle drivability has a major impact on the driver's physiological reactions. Moreover, typical physiological features may serve as indicators of different aspects of vehicle performance. The future research will discuss more parameters and verify their effects.

References

Brookhuis KA, De Waard D, Janssen WH. Behavioural impacts of advanced driver assistance systems–an overview. European Journal of Transport and Infrastructure Research 2001; 1(3):245-53.

Data S, Frigerio F. Objective evaluation of handling quality. Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering 2002; 216(4): 297-305.

De Luca CJ. The use of surface electromyography in biomechanics. Journal of Applied Biomechanics 1997;13(2):135-63.

Farah G, Hewson D, Duchene J. Surface electromyography as a tool to assess the responses of vehicle passengers to lateral accelerations: Part I. Extraction of relevant muscular activities from noisy recordings. Journal of Electromyography and Kinesiology 2006; 16(6): 669-76.

Farah G, Petit-Boulanger C, Hewson D, Duchêne J. Surface electromyography as a tool to assess the responses of vehicle passengers to lateral accelerations. Part II: Objective comparison of vehicles, Journal of Electromyography and Kinesiology 2006; 16(6): 677-84.

Gao ZH, Li CZ, Hu HY, Zhao H, Chen CY, Yu HL. Experimental study of young male drivers' responses to vehicle collision using EMG of lower extremity. Bio-medical Materials and Engineering 2015; 26(s1): S563-73.

Gao ZH, Li CZ, Hu HY, Zhao H, Chen CY, Yu HL. Study of the influence of muscle activation on a driver's lower extremity injury. International Journal of Crashworthiness 2016; 21(3): 191-97.

Gheorghe LA, Takashi S. Brain waves measurement based evaluation of mental workload related to visual information while driving. SAE International Journal of Passenger Cars-Mechanical Systems 2011; 4(2011-01-0593): 578-85.

Gómez G, Nybacka M, Drugge L, Bakker E. Machine learning to classify and predict objective and subjective assessments of vehicle dynamics: the case of steering feel. Vehicle System Dynamics 2016; 56(1): 150-71.

Haufe S, Treder M, Gugler M, Sagebaum M., Curio G, Blankertz B. EEG potentials predict upcoming emergency brakings during simulated driving. Journal of Neural Engineering 2011; 8(5): 056001.

Kolich M. Using Failure Mode and Effects Analysis to design a comfortable automotive driver seat. Applied Ergonomics 2014; 45(4): 1087-96.

Liu YH. Method for measuring a driver's steering efficiency using electromyography. Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering 2014; 228(10): 1170-84.

Mastrigt S, Kamp I, Veen S, Vink P, Bosch T. The influence of active seating on car passengers' perceived comfort and activity levels. Applied Ergonomics 2015; 47: 211-19.

Matsushita A, Takanami K, Takeda N, Takahashi M. Subjective evaluation and vehicle behavior in lane-change maneuvers. SAE Technical Paper 1980: 800845.

Mo SM, Hyun Y, Kim CS, Kim DM, Kang HS. Correlation between muscle contraction and vehicle dynamics in a real driving. Advances in Affective and Pleasurable Design 2012:196-201.

Nash C, Cole, DJ, Bigler R. A review of human sensory dynamics for application to models of driver steering and speed control. Biological Cybernetics 2016; 110(2-3): 91-116.

Nash CJ, Cole DJ. Modelling the influence of sensory dynamics on linear and nonlinear driver steering control. Vehicle System Dynamics 2017:1-30.

Pick AJ, Cole DJ. Driver steering and muscle activity during a lane-change manoeuver, Vehicle System Dynamics 2007; 45(9): 781-805.

Rothhämel M, Ijkema J, Drugge L. A method to find correlations between steering feel and vehicle handling properties using a moving base driving simulator. Vehicle System Dynamics 2011; 49(12): 1837-54.

Shi GB, Zhang X, Lin Y. Subjective fuzzy evaluation of steering feel for electric power steering system. Journal of Jilin University (Engineering and Technology Edition) 2007; 37(4): 751-55.

Sinclair J, Taylor P, Hebron J, Brooks D, Hurst H, Atkins S. The reliability of electromyographic normalization methods for cycling analyses. Journal of Human Kinetics 2015; 46(1): 19-27.

Smith ME, Gevins A, Brown H, Karnik A, Du R. Monitoring task loading with multivariate EEG measures during complex forms of human-computer interaction. Human Factors 2001; 43(3): 366-80.

Yang GS, Yingzi L, Prabir B. A driver fatigue recognition model based on information fusion and dynamic Bayesian network. Information Sciences 2010; 180(10): 1942-54.

Zhang X, Shi GB. Objective evaluation of electric power steering steering feel, Journal of Mechanical Engineering 2009; 45(9): 171-75.

Zheng RC, Nakano K, Okamoto Y, Ohori M, Hori S, Suda Y. Evaluation of Sternocleidomastoid Muscle Activity of a Passenger in Response to a Vehicle's Lateral Acceleration While Slalom Driving. IEEE Transactions on Human-Machine Systems 2013; 43(4): 405-15.